Applied Energy xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Catch energy saving opportunity (CESO), an instantaneous optimal energy management strategy for series hybrid electric vehicles

A. Rezaei[a,*], J.B. Burl[a], A. Solouk[b], B. Zhou[a], M. Rezaei[c], M. Shahbakhti[b]

[a] Electrical Engineering Department, Michigan Technological University, Houghton, MI 49931, USA
[b] Mechanical Engineering-Engineering Mechanics, Michigan Technological University, Houghton, MI 49931, USA
[c] Electrical Engineering Department, Wayne State University, Detroit, MI 48202, USA

HIGHLIGHTS

- Novel instantaneous energy management strategy for series hybrid electric vehicles.
- Finds a range for optimal equivalent factor of equivalent consumption minimization strategy.
- The strategy needs less calibration in comparison with existing instantaneous strategies.
- Simulation Model is developed based on experimental setup of powertrain components.

ARTICLE INFO

Keywords:
Hybrid electric vehicle
Energy management
Optimal control
ECMS
Pontryagin's minimum principle
Fuel economy

ABSTRACT

This paper introduces a new energy management (EM) strategy for series hybrid electric vehicles (HEVs). Series HEVs operate in charge-depletion mode and then switch to the charge-sustaining mode in which the battery state of charge (SOC) is maintained within a certain range. The proposed EM strategy in this paper is a form of adaptive equivalent consumption minimization strategy (ECMS) that is designed for the charge-sustaining mode. The EM strategy defines soft bounds on the battery SOC and is penalized for exceeding these bounds. But, to catch energy-saving opportunities (CESOs), the EM strategy allows SOC to exceed the soft bounds. Thus, the introduced EM strategy is named ECMS-CESO. In addition, a range for the ECMS optimal equivalent factor is proposed for series HEVs. The proposed range is used in deriving the formula for calculating the adaptive equivalent factor. The main advantage of the proposed EM strategy is that ECMS-CESO can achieve close to optimal fuel economy without the need for predicting future driver demand. Since there is no need for prediction, the intensive calculations for finding the optimal control over the prediction horizon can be eliminated. Therefore, implementation of ECMS-CESO is easily feasible for real-time applications. Experimental powertrain data is collected to develop a powertrain model for a series HEV in this study. Simulation results on several drivecycles show that, on average, the fuel economy achieved by ECMS-CESO is within 6% of the maximum fuel economy. In addition, comparing ECMS-CESO with two existing adaptive ECMSs shows up to 5% improvement in fuel economy, on average.

1. Introduction

The transportation sector is one of the main sources of greenhouse gas emissions and global warming [1,2]. To comply with new environmental regulations, many technologies are introduced to reduce fuel consumption and pollutant emissions in transportation sector [3,4]. Hybridizing the vehicle powertrain is one of the technologies to improve vehicle fuel economy and reduce greenhouse gas emissions [5]. In addition to liquid fuel, hybrid electric vehicles (HEVs) are equipped with at least one renewable energy source like batteries or super-capacitors. The existence of at least two energy sources in HEVs necessitates an energy management (EM) strategy for dividing the driver-demanded power among the available power sources efficiently. Many studies have shown that energy management strategies have a considerable impact on HEV fuel consumption [6–11].

Different EM strategies for HEVs include: Rule-based control (RBC) [12,13,8,14], equivalent consumption minimization strategy (ECMS) [15–20,9], model predictive control (MPC) [21–27], and globally

* Corresponding author.
E-mail addresses: arezaei@mtu.edu (A. Rezaei), burl@mtu.edu (J.B. Burl), asoloukm@mtu.edu (A. Solouk), binz@mtu.edu (B. Zhou), mohammad.rezaei@wayne.edu (M. Rezaei), mahdish@mtu.edu (M. Shahbakhti).

http://dx.doi.org/10.1016/j.apenergy.2017.09.089
Received 9 April 2017; Received in revised form 13 September 2017; Accepted 14 September 2017
0306-2619/

Nomenclature

Abbreviations

A-ECMS	adaptive ECMS
BSFC	brake specific fuel consumption
CESO	catch energy-saving opportunities
DP	dynamic programming
ECMS	equivalent consumption minimization strategy
EM	energy management
GPS	global positioning system
HEV	hybrid electric vehicle
HWFET	highway fuel economy test
MPC	model predictive control
MPG	miles per gallon
SOC	state of charge
RBC	rule-based control
SI	spark ignition
UDDS	urban dynamometer driving schedule

Symbols

λ	ECMS equivalent factor [–]
t	time [s]
U	space of the admissible controls
$\mathbf{u}_{eom}$	engine only mode control action
$\mathbf{u}_{bom}$	battery only mode control action
$\mathbf{u}_{cm}$	charging mode control action
$\mathbf{u}_{hm}$	hybrid only mode control action
$\mathbf{u}$	control actions vector
$\mathbf{x}$	state vector
$\dot{m}_{fuel}$	fuel mass flow rate [g/s]
t_f	final time [s]
P_D	driver-demanded power on the wheels [W]
P_{ptr}	power of powertrain at the wheels [W]
P_{brk}	friction brake system power [W]
P_{em}	E-machine mechanical power [W]
P_{gn}	generator electrical power [W]
$P_{bat,C}$	battery pack chemical power [W]
$P_{bat,E}$	battery pack electrical power [W]
r_{trs}	transmission gear ratio [–]
i_{bat}	battery pack current [A]
$V_{bat,oc}$	battery pack open circuit voltage [V]
Q_{bat}	battery pack capacity [A· s]
Q_{lhv}	fuel lower heating value [J/s]
SOC_L	SOC lower constraint [–]
SOC_H	SOC upper constraint [–]
SOC_L^{soft}	SOC lower soft constraint [–]
SOC_H^{soft}	SOC upper soft constraint [–]
x_1	battery SOC [–]
x_2	defined to augment the cost function [–]
x_1^{sp}	target SOC [–]
H	Hamiltonian function
η	efficiency [–]
R_{bat}	battery internal resistance [Ω]
p	costate variable

Subscripts and Superscripts

*	optimal value
bat	battery
blt	belt
bom	battery only mode
brk	brake
chg	charge
cm	charging mode
D	driver demand
dis	discharge
e	electric energy path
eng	engine
em	E-machine
eom	engine only mode
f	fuel energy path
fuel	fuel
gn	generator
H	high
hm	hybrid mode
*inv*1	inverter #1
*inv*2	inverter #2
L	low
lhv	lower heating value
min	minimum
max	maximum
ptr	powertrain
trs	transmission

optimal contol [22,28,29].

Globally optimal control yields the maximum fuel economy for a HEV. The globally optimal controller requires knowledge of the reference signal, i.e. the driver-demanded power, over the entire drivecycle. Therefore, the globally optimal controller is non-causal. Attempts to predict the reference signal (make this controller causal) yield uncertainty [30–32] and result in significantly degraded performance [33,34]. Therefore, instead of finding the globally optimal solution, causal EM strategies, that are realizable, have been studied widely in this field. Causal EM strategies yield a sub-optimal solution for HEVs. The causal energy managements for HEVs can be divided into two main groups: EMs designed based on experimental rules/tests (like RBC), and EMs designed based on optimal control theories (like MPC and ECMS). There are many different EM strategies in each of these two main categories. The EM strategy proposed in this paper is an instantaneous optimal controller based on ECMS. Therefore, like all *causal* EM strategies, the proposed EM strategy is not globally optimal and yields a sub-optimal solution.

The globally optimal controller can be formed using dynamic programming (DP) for HEVs. DP is a numerical approach for finding the optimal solution in control theory [28]. Extending DP to the problem of energy management for HEVs requires the full *advanced* knowledge of the vehicle speed and the road conditions. Due to lack of this prior information, DP is mostly employed for simulations to evaluate the performance of other EM strategies [35].

In the automotive industry, RBC is the most popular EM strategy [13,36]. RBC is realized by a state machine or an if-else structure. Therefore, designing RBC is an intuitive expert level procedure with straight forward implementation. However, tuning the thresholds for the rules of the state machine or the if-else structure requires extensive simulations and experimental tests on the vehicle [13]. In addition, different studies show the performance of RBC is poor in comparison with optimal EM strategies like DP, MPC, or ECMS [6,9,24,37]. To improve the RBC performance, an state-of-the-art approach is to extract the rules from stochastic DP [12,14]. However, gathering data for the stochastic DP and then extracting the rules are challenging. In addition, the extracted rules are still dependent on the original database and the achieved RBC can still perform poorly on a new drivecycle.

In MPC, at each moment a short horizon of driver-demanded power P_D in the future is predicted. Then an optimization algorithm is